Fit between humanitarian professionals and project requirements: hybrid group decision procedure to reduce uncertainty in decision-making

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Fit Between Humanitarian Professionals and Project Requirements: Hybrid Group Decision Procedure to Reduce Uncertainty in Decision-Making

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Abstract

Choosing the right professional that has to meet indeterminate requirements is a critical aspect in humanitarian development and implementation projects. This paper proposes a hybrid evaluation methodology for some non-governmental organizations enabling them to select the most competent expert who can properly and adequately develop and implement humanitarian projects. This methodology accommodates various stakeholders' perspectives in satisfying the unique requirements of humanitarian projects that are capable of handling a range of uncertain issues from both stakeholders and project requirements. The criteria weights are calculated using a two-step multi-criteria decision-making method: (1) Fuzzy Analytical Hierarchy Process for the evaluation of the decision maker weights coupled with (2) Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank the alternatives which provide the ability to take into account both quantitative and qualitative evaluations. Sensitivity analysis have been developed and discussed by means of a real case of expert selection problem for a non-profit organisation. The results show that the approach allows a decrease in the uncertainty associated with decision-making, which proves that the approach provides robust solutions in terms of sensitivity analysis.

Keywords: Expert selection; humanitarian projects; multi-criteria decision-making; Fuzzy Analytic Hierarchy Process, **TOPSIS**.

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1. Introduction

Humanitarian development projects are being implemented to fulfil various objectives and several aims. They are mainly intended to improve the well-being of people and satisfy the unprecedented demand for health, food, energy, and so on (Amadei and Sandekian 2010). Humanitarian development projects, especially in the developing world characterized by a lack in the infrastructures and technologies, which make it a complex working environment, require inputs from the experts' experience and diverse types of skills and knowledge related to particular scientific and industrial fields. Indeed, one of the key factors in the successful implementation of such projects lies in the selection of experts. Due to the complex nature of humanitarian projects (Walker and Russ 2010), experts can be appointed to work on a large variety of tasks, such as improving hygienic circumstances in health care facilities, or, on a broader basis, educating people on health subjects, educating children, instructing on behavioural subjects, leading community empowerment projects, enhancing the self-empowerment of specific groups, or working on a preventive approach of health in communities. On the other hand, experts can also be hired to be in charge of technical or infrastructural projects like construction, transportation systems, and implementation of renewable energy, among many others (Amadei and Wallace 2009). Given the pivotal role of human capital in the success of firms and projects (Kiessling and Harvey 2005), the issue of recruiting skilled experts and personnel have received more attention in recent years by researchers (Billsberry 2008; Breaugh et al. 2008; Rouyendegh and Erkan 2013). Significantly, experts should not only have the necessary specialized knowledge and experience but they also need to be versatile and capable of dealing with a variety of circumstances that may potentially necessitate different cultural and linguistic backgrounds. All these factors lead to a number of criteria that needs to be taken into consideration when evaluating an expert's candidature for a specific position linked to a humanitarian development project. Due to the nature of a humanitarian project and the geographical environment in which it can be implemented, the decision makers can add or remove some criteria, and it is more convenient for them to refer to the values they require and the importance assessment by means of a common and shared language

In the case of non-governmental organisations (NGO's), the decision of selecting a specific expert for a particular humanitarian development project is often made by a management board composed of people involved in the execution of the programme or members of the institution in which they evolve. In such a case, the situation involves then a group of decision makers rather than a single decision maker. This group of decision makers is constituted of members who have different backgrounds and field expertise. Each one of them has their distinctive and typical characteristics with regards to the criteria. This implies that for any given situation, the decision makers will usually have diverse or distinctly dissimilar decisions due to the distinguishable differences in their insights and opinions and the multi-criteria nature with the presence of both quantitative and qualitative factors which makes the problem more complex (Koutra et al. 2017). The same applies for the range of criteria that needs to be matched with the requirements for humanitarian projects as well as for the assessment of the criteria themselves with respect to the experts.

However, to the best of our knowledge, there are practically no studies focusing on the match between expert's selections criteria and the requirements expected for humanitarian development projects.

In order to fill in this research gap, this paper aims to develop a group decision-making approach to select experts for humanitarian development projects based on multiple subjective and objective criteria.

The rest of the paper is organised as follows. Section 2 provides a literature review associated with expert selection and the methodologies employed by various researchers. Section 3 gives a comprehensive presentation of the scientific background and methodology developed. Section 4 offers a real application of the approach with the experimental results from a case that involved four decision makers with six criteria in order for them to choose one of the five proposed experts. Section 5 discusses the sensitivity analysis and comparison of the achieved results. Finally, the paper ends with a conclusion and some suggestions for future research directions.

2. Literature review

2.1. Expert selection and humanitarian field

Expert selection can be defined as the choosing process of individuals who match the qualifications required to perform a defined job in the best way possible (Dursun and Karsak 2010). The process itself involves subjectivity, validity, and criteria fixing (Canós and Liern 2008; Tavares 1994). The general problem of selection decision, where some or all the information are subjective, is addressed by Zahedi (1987), and a substantial amount of information regarding the personnel selection problem and the techniques used to solve it is developed by Liang and Wang (1992). On the other hand, staff selection is discussed in some studies (Smith et al. 2002; Rouyendegh and Erkan 2013) dealing with actual application of academic staff selection using the opinion of experts to be applied into a model of group decision. Significantly, very few studies offer a coherent comparison between the different methods in the field of staff or personnel selection within organizations (Aziri et al. 2014). Furthermore, these studies concentrate on staff recruitment in the absence of standards, and are consisted of process-oriented descriptions. Additionally, for humanitarian development and aid purposes, those papers focus on the selection of facilities and tangible assets, and not on the experts that may help in the development of the project itself; such as the development and implementation of healthcare facilities and hospitals (Brent et al. 2007; Tsai and Chou 2009; Karagiannidis et al. 2010; Lu et al. 2016), emergency shelters location (Trivedi and Singh 2017; Xu et al. 2016), corresponding funding models (Tavana 2007) or locating refugees camps (Çetinkaya et al. 2016).

In the humanitarian field, decision-making has always been considered as a critical issue due to the large variety of complexities it involves, such as natural disasters preparedness or responses and the resulting impact on people (Goldschmidt and Kumar 2017; Prasad et al. 2017), where research directions have been suggested in (Benini et al. 2009; Peng and Yu 2014). Recent devastation through natural calamities had forced existing studies to open up discussions on humanitarian operations where numerous critical open questions have been thrown out by academic through systematic review articles (Altay and Green 2006; Galindo and Batta 2013; Banomyong et al. 2017; Oloruntoba et al. 2016; Gutjahr and Nolz 2016). Given this context, and to the best knowledge of the authors, there is no work focusing on the selection of experts for the development of projects in the humanitarian field. However, several multi-criteria

decision-making (MCDM) and optimization models are developed in order to provide decision makers (DMs) in humanitarian aid with suitable decision support (Caunhye et al. 2012; Vitoriano et al. 2011; Travidi and singh 2017; Hosseini et al. 2016). In the literature related to operations-research approaches to humanitarian operations, many optimization criteria have been employed, such as (I) efficiency criteria, (II) effectiveness criteria, and (III) equity criteria (Gralla et al. 2014). On the other hand, Sgarbossa et al. (2015) present a general MCDM framework to assist decision makers in the evaluation of humanitarian operations issues in which the objective hierarchy is defined.

2.2. Methodologies and applications developed

In terms of methodology, fuzzy approaches are applied satisfactorily for selection and evaluation problems (Alguliyev et al., 2015; Baykasoğlu et al. 2017). In fact, fuzzy set theory appears as an essential tool to provide a decision method that incorporates imprecise judgment inherent to the personnel selection process (Karsak 2001). Expert selection for humanitarian development projects has imprecise or vague elements both in evaluating the experts as well as their competency to undertake humanitarian projects. However, the degree of uncertainty, or level of fuzziness, is almost never justified nor investigated. Both crisp and fuzzy Analytical Hierarchy Processes (AHP) have often been suggested to deal with the selection problems (e.g., Güngör et al. 2009; Özcan et al. 2011; Özdağoğlu and Özdağoğlu 2007; Wang et al. 2017; Kirubakaran and Ilangkumaran 2016). A comparison of crisp AHP and fuzzy AHP (FAHP) with a case study examining the selection of shop floor workers is documented in Özdağoğlu and Özdağoğlu (2007). On the other hand, Chandran et al. (2005) outline the limitations of AHP in the evaluation of criteria weights using linear programming models. The main limitation being that the criteria are considered as independent. To tackle this limitation, Huang et al. (2008) suggest using Analytical Network Process (ANP) to deal with dependencies. In fact, ANP can deal with the interrelationships that exist among criteria and several works dealing with personnel selection using ANP technique are proposed such as (Lin 2010) where the authors deals with the inner dependences among the criteria in the ANP phase using pairwise comparison matrices. Also Kabak et al. (2012) proposed a methodology for sniper selection using a combination of fuzzy ANP, fuzzy TOPSIS and fuzzy ELECTRE (Elimination and Choice Expressing Reality) techniques.

For the ANP limitation, researchers also draw attention to the way traditional fuzzy ANP deals with dependences. First, establishing a suitable network structure can be very difficult. Second, the process of constructing pairwise comparison deriving the dependences between the criteria is unnatural and cumbersome, as there are more than four criteria, and thus it can lead to inconsistencies for group decision-making processes as shown by Limayem and Yannou (2007). Karsak (2001) proposes a fuzzy MCDM framework based on the concepts of ideal and anti-ideal solutions for the personnel selection process. He incorporates data in the forms of linguistic variables, triangular fuzzy numbers and crisp numbers into the personnel selection-decision analysis. Chen and Cheng (2005) propose a new approach to rank fuzzy numbers by metric distance for selecting information system personnel.

For the evaluation of alternatives against criteria, TOPSIS is extensively used for the personnel selection problem (Dursun and Karsak 2010, Polychroniou and Giannikos 2009). A fuzzy TOPSIS approach

to managers' selection with three new concepts (namely, relative importance of DMs per criterion, similarity-proximity degree among the decision makers, and veto thresholds) is proposed by Kelemenis et al. (2011). Interestingly, it was also shown that using different distance measurements, such as Yager's Sign distance in TOPSIS, can change the ranking of the alternatives (Kelemenis and Askounis 2010). Liu et al. (2015) suggested an extended VIKOR (Multicriteria Optimization and Compromise Solution) method, combined with interval 2-tuple linguistic variables, to choose appropriate individuals among candidates in a group decision-making environment under uncertain and incomplete linguistic information. In the evaluation process, the ratings of the candidates are represented as interval 2-tuple linguistic variables. The VIKOR method is used to obtain the ranking of candidates and to find an optimal individual for personnel selection. In the same context of using fuzzy TOPSIS, Boran et al. (2011) present a multi-criteria group decision-making process to select appropriate personnel among candidates to a sales manager position in a manufacturing company. In the evaluation process, the ratings of the candidates are represented as intuitionistic fuzzy numbers. Also other methods applied to personnel selection and evaluation are found in the literature. Haghighi et al. (2012) propose an employee evaluation and selection approach, based on fuzzy multiple attribute decision-making through triangular fuzzy numbers, to evaluate the most adequate employee through the rating of both qualitative and quantitative criteria. Canós and Liern (2008) develop a flexible decision support system simulating experts evaluations using ordered, weighted average aggregation operators, which assign different weights to different selection criteria to help managers in their decision making for personnel selection. Kelemenis and Askounis (2010) propose a new TOPSIS based multi-criteria approach to personnel selection, incorporating a new measurement for the ranking of the alternatives, based on the veto concept, a critical characteristic of the main outranking methods. Qualitative information of each suitable candidate is expressed by a 2-tuple linguistic variable. Dursun and Karsak (2010) propose a MDCM algorithm using the principles of fusion of fuzzy information, 2-tuple linguistic representation model, and TOPSIS technique in order to manage the information assessed using both linguistic and numerical scales.

In terms of applications, the existing research covers different domains with regard to the importance of personnel selection, which represents one of the organizations' success factors. Several applications are found in the literature. For instance, Sadatrasool et al. (2016) develop a MCDM and statistical model for the selection of project manager for petroleum industry. Chaghooshi et al (2016) propose a VIKOR and DEMATEL (Decision Making Trial and Evaluation Laboratory) based hybrid fuzzy approach for the selection of a project manager for an Iranian food company. For personnel selection in IT companies, Erdem (2016) proposes a fuzzy hierarchy process method and Aggarwal (2013) suggests a new AHP weighted fuzzy linear-programming model. Bose and Chadtterjee (2016) provide a fuzzy hybrid-MCDM approach for the selection of wind-turbine service technicians. Dadelo et al. (2012) offer a model for the selection of elite security personnel. Capaldo and Zollo (2001) propose a fuzzy model to improve the effectiveness of personnel assessment within a large Italian company. Golec and Kahya (2007) propose a competency-based fuzzy model to minimize subjective judgment in multifactor, competency-based measures in a hierarchical structure.

Nonetheless, as far as we are concerned, we could not find any studies investigating the match between expert's selections criteria and the requirements expected for humanitarian development projects. Our paper would then fit in filling this research gap by developing a group decision-making approach to pick experts for humanitarian development projects based on multiple subjective and objective criteria.

3. Hybrid methodology and theoretical background

In most of the situations related to expert selection for humanitarian development projects where a decision must be made, it is rare for the DMs to have in mind a clear single criterion. Thus, when a DM is part of a group decision-making process, it is even rarer to be a priori a single, well-defined criterion deemed acceptable by all actors to guide the process (Figueira et al. 2005). Such situations refer back to the group MCDM problems. In this respect, the present paper aims then at exploring innovative aspects of expert selection for humanitarian development projects, characterized by specific criteria that have to be considered to comply with the requirements of most funding humanitarian organizations and agencies. In this regard, Figure 1 present our adopted four-step group-based methodology designed and developed to tackle the complexity of the problem:

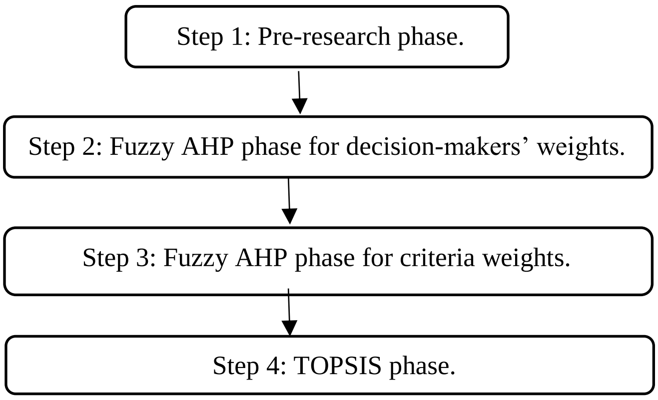

Figure 1. Proposed methodology

The proposed methodology draws on various works dealing with hybrid approaches based on AHP and TOPSIS. For instance, in (Dağdeviren et al. 2009) the authors proposed a 3-step model; step 1 identifies the criteria, step 2 compares the criteria using AHP, and step 3 evaluates alternatives using fuzzy TOPSIS to determine the final rank. Another work using multi-steps methodology is proposed by Işıklar and Büyüközkan (2007), where the authors proposed a group decision-making approach for phone selection. The methodology proposed is composed of three steps: (1) identify mobile phone selection criteria; (2) calculate the criteria weights; (3) final rank of alternatives using TOPSIS technique. While going through the literature survey, we were unable to identify any work dealing with expert selection for humanitarian projects.

The proposed methodology uses the concepts of multiple-criteria group decision-making and fuzzy sets theory. The approach takes advantage of FAHP for weighting the decision makers as well as the criteria considered, and of TOPSIS in ranking the alternatives. Indeed, since criteria and experts weighting is a process based on subjective assessments, an adequate way to obtain decision-maker's judgments is to perform pairwise comparison, which is one of the most important features of AHP. Moreover, due to the quantitative and qualitative natures of the criteria, fuzzy formulations of AHP are more adequate than crisp AHP. Furthermore, TOPSIS (Hwang and Yoon 1981) is a widely accepted multi-attribute decision-making technique for ranking different alternatives for a considered problem. Among the advantages of TOPSIS are (1) the logical representation of the rational of human choice by considering both the best and the worst attributes of alternatives simultaneously (represented by a scalar value), and (2) the simplicity on computation and presentation (Shih et al. 2007). The number of attributes does not influence the number of steps, thus it offers a faster solution (Ic 2012). In recent years, TOPSIS has been successfully applied as decision-making tools to different areas, including water management (Srdjevic et al. 2004), transportation planning (Janic 2003), human resource (Shih et al. 2007), mechanical engineering (Milani et al. 2005), manufacturing engineering (Kwong and Tam 2002), and policies development (Qin et al. 2008). In the chemical engineering field, this technique has been combined with optimization procedures to identify the best options considering economic and environmental factors (Li et al. 2009). The above four steps are presented in detail in the following subsections.

3.1. Step 1: Pre-research Phase

In the pre-research phase, a list of the criteria used to select an expert for humanitarian projects is established. Indeed, from a humanitarian organisation's point of view, the expert has the decision-making power governing the field work and the responsibility of implementing the project objectives (Krause 2014). Thus, the selection is based on the concordance and the coherence of the criteria with the requirements of humanitarian and social development projects (Bierschenk and Olivier de Sardan 2003; Rondinelli 2013). Six criteria are identified below.

- **C1**: *Work experience*: the experience that a person has accumulated from working in a specific field. Put differently, this criterion covers the previously accomplished jobs and the experience obtained from these jobs. In many cases, a certain degree of work experience is a prerequisite for the assignment of an expert to a humanitarian development project.
- **C2**: *Education*: a process in which a person accumulates knowledge, skills, and values out of a given context. The criterion evaluates the educational level and diplomas obtained by the different experts.
- **C3**: *Satisfaction from past projects*: experts who had already been assigned to projects in the past can be evaluated through the level of their employers' satisfaction or can provide proof of success. It is closely linked to the way earlier projects have been conducted and managed until their success.
- **C4**: *Motivation*: a kind of energy that enables the experts to achieve their goals, to which can be added the willingness to engage oneself in a project and the interest in the project. It partially provides answers to questions like "why does a person apply for a specific project?" By analysing the motivation, further social commitment of the expert, which has not been considered in the experience criterion, can also be taken into account. Due the nature of the job, some examples such as working as a volunteer, or participating in humanitarian and social associations, NGOs, or NPOs, can also be cited.
- **C5**: *Compensation*: this is one of the basic criteria used to make a choice. Humanitarian and social projects are often bound to a limited budget. The funding is often collected through donations or directly allocated

by non-governmental, governmental, or industrial organizations. Therefore, the remuneration of the experts, in particular the salary expected by an expert, can become an important criterion.

- **C6**: *Capacity of integration*: the capacity to adapt someone's behaviour, language, and appearance to the host country or region, and the interest towards the social and cultural issues. Indeed, transmitting ideas and managing projects requires a certain degree of acceptance and integration among the host community.

At a first glance, these six criteria may seem independent. However, since the work deals with humans whose nature is generally characterised by complexity and diversity, it may be interesting as well to consider these criteria as dependent. For the first assumption, fuzzy AHP is adapted to deal with independent criteria with ambiguity in their evaluation, where for the second assumption, ANP seems to be a good technique to be used for the criteria weight evaluation.

3.2. Step 2: Fuzzy AHP Phase for Decision Makers' weights

The group consists of four decision makers, denoted as DM 1, DM 2, DM 3 and DM 4. A decision maker who knows all the other ones is appointed to assess each one's importance and expertise level, and makes a pairwise comparison between decision makers on a linguistic scale basis. The linguistic assessments are then converted into triangular fuzzy numbers for Fuzzy AHP evaluations. AHP technique essays the qualitative and the quantitative indices efficiently (Rao and Davim 2008). This method is advantageous since it does not only rely on the usage of qualitative criteria in decision-making but also allows for presenting the results quantitatively through mathematical techniques, communicating the issues at hand, enhancing the reliability of findings, managing and resolving the different complications, getting the thoughts of the members involved in making decision, collecting the findings of experts to decide on the best alternative, and ranking according to the pairwise comparisons of criteria (Asghari et al. 2017).

The combination of AHP and fuzzy logic, and the use of fuzzy numbers is a means designed to obtain more decisive judgments by prioritizing the expert selection criteria and weighting them in the presence of vagueness. Several fuzzy AHP applications in the literature recommend systematic approaches for the selection of alternatives, and explanation of the problematic by means of a fuzzy set theory and hierarchical structure analysis (Kabir and Akhtar Hasin 2011). As a result of the fuzzy nature of the assessment process, it is more appropriate for decision makers to propose an interval judgment than a fixed value (Bozdağ et al. 2003). This study focuses on a fuzzy AHP approach introduced by Chang (1992), in which triangular fuzzy numbers are preferred for pairwise comparison scale. Extent analysis method is selected for the synthetic extent values of the pairwise comparisons as follows:

A fuzzy number is a special fuzzy set $F = \{(x, \mu_F(x), x \in \mathbb{R})\}$, where x takes its values on the real line, $\mathbb{R}: -\infty < x < \infty$ and $\mu_F(x)$ is a continuous mapping from $\mathbb{R}$ to the closed interval [0, 1], called membership function. A Triangular Fuzzy Number (TFN) expresses the relative strength of each pair of elements in the same hierarchy and can be denoted as $M = (l, m, u)$, where $l \leq m \leq u$ The parameters *l*, *m* and *u* indicate, respectively, the smallest possible value, the most promising value, and the largest possible value in a fuzzy event. Triangular type membership function of *M* fuzzy number can be described as in Equation (1). When $l = m = u$, it is a non-fuzzy number by convention.

$$MM(x) = \begin{cases} 0 & x < l \\ (x-l)/(m-l) & l \le x \le m \\ (u-x)/(u-m) & m \le x \le u \\ 0 & x > u \end{cases} \tag{1}$$

A linguistic variable is a variable whose values are expressed in linguistic terms. The concept of a linguistic variable is very useful in dealing with situations, which are too complex or not well defined to be reasonably described in conventional quantitative expressions (Zadie 1965; Zimmermann 2011; Kauffmann and Gupta 1991; Soner et al. 2012). In this study, the linguistic variables used in the model can be expressed in positive TFNs for each criterion as shown in Figure 2. The linguistic variables matching TFNs and the corresponding membership functions are provided in Table 1. The proposed methodology employs a scale of fuzzy numbers from $\tilde{1}$ to $\tilde{9}$ symbolize with tilde (~) as triangular fuzzy numbers. Table 1 illustrates AHP and fuzzy AHP comparison scale considering the linguistic variables that describe the importance of attributes and alternatives to improve the scaling scheme for the judgment matrices.

Linguistic scale for importance	**Fuzzy numbers for fuzzy AHP**	**Membership function**	**Domain**	**Triangular fuzzy scale (*l*, *m*, *u*)**
Equal importance	$\tilde{1}$	$\mu_M(x) = (x - \frac{1}{3})/(1 - \frac{1}{3})$ $\mu_M(x) = (3 - x)/(3 - 1)$	$\frac{1}{3} \le x \le 3$ $1 \le x \le 3$	(0.33, 1.0, 3.0)
Weak importance of one over another	$\tilde{3}$	$\mu_M(x) = (x - 1)/(3 - 1)$ $\mu_M(x) = (5 - x)/(5 - 3)$	$1 \le x \le 3$ $3 \le x \le 5$	(1.0, 3.0, 5.0)
Essential or strong importance	$\tilde{5}$	$\mu_M(x) = (x - 3)/(5 - 3)$ $\mu_M(x) = (7 - x)/(7 - 5)$	$3 \le x \le 5$ $5 \le x \le 7$	(3.0, 5.0, 7.0)
Very strong importance	$\tilde{7}$	$\mu_M(x) = (x - 5)/(7 - 5)$ $\mu_M(x) = (9 - x)/(9 - 7)$	$5 \le x \le 7$ $7 \le x \le 9$	(5.0, 7.0, 9.0)
Extremely preferred	$\tilde{9}$	$\mu_M(x) = (x - 7)/(9 - 7)$	$7 \le x \le 9$	(7.0, 9.0, 9.0)
Intermediate values between the two adjacent judgments.				
If factor *i* has one of the above numbers assigned to it when compared to factor *j*, then *j* has the reciprocal value when compared with *i*				Reciprocals of above $M_1^{-1} \approx (1/u_1, 1/m_1, 1/l_1)$

Table 1. Linguistic variables describing weights of attributes and values of ratings.

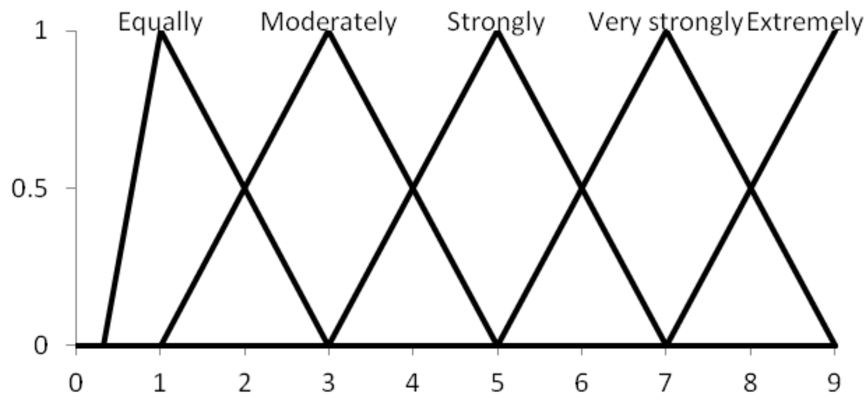

Figure 2. Linguistic variables and membership function of each criterion.

By using triangular fuzzy numbers via pairwise comparison, the fuzzy judgment matrix $\tilde{A}(a_{ij})$ can be expressed mathematically as in Equation (2).

$$\tilde{A} = \begin{cases} 1 & \tilde{a}_{12} & \tilde{a}_{13} & \dots & \tilde{a}_{1(n-1)} & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \tilde{a}_{23} & \dots & \tilde{a}_{2(n-1)} & \tilde{a}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ \tilde{a}_{(n-1)1} & \tilde{a}_{(n-1)2} & \tilde{a}_{(n-1)3} & \dots & 1 & \tilde{a}_{(n-1)n} \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \tilde{a}_{n3} & \dots & \tilde{a}_{n(n-1)} & 1 \end{cases} \tag{2}$$

The judgment matrix $\tilde{A}$ is $n \times n$ fuzzy matrix containing fuzzy numbers $\tilde{a}_{ij}$ as shown in Equation (3).

$$\tilde{a}_{ij} = \begin{cases} 1, & i = j \\ \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} \text{ or } \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1}, & i \neq j \end{cases} \tag{3}$$

Let $X = \{x_1, x_2, ..., x_n\}$ be an object set, whereas $U = \{u_1, u_2, ..., u_n\}$ is a goal set. According to fuzzy extent analysis, the method can be performed with respect to each object for each corresponding goal, resulting in *m* extent analysis values for each object, given as $M_{g_i}^1, M_{g_i}^2, ..., M_{g_i}^m$ (for *i* = 1, 2, … , *n*), where all the $M_{g_i}^j$ (for *j* = 1, 2, … , *m*) are triangular fuzzy numbers representing the performance of the object x_i with regard to each goal u_j. The steps of Chang's extent analysis (1992) can be detailed as follows (Kahraman et al., 2003; Bozbura et al., 2007):

__Step 1__**:** The fuzzy synthetic extent value with respect to the i^{th} object is defined as:

$$S_i = \sum_{j=1}^{m} M_{g_i}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1} \tag{4}$$

where $\otimes$ is a fuzzy multiplication operator. To obtain $\sum_{j=1}^{m} M_{g_i}^{j}$, perform the fuzzy addition operation *m* extent analysis values for a particular matrix such that

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right) \tag{5}$$

To obtain $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$, perform the fuzzy addition operation of $M_{g_i}^{j}$ ($j = 1, 2, ..., m$) values such that

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i\right) \tag{6}$$

and then compute the inverse of the vector in Equation (6) such that

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \tag{7}$$

<u>Step 2</u>: The degree of possibility of $M_2 \geq M_1$ is defined as:

$$V(M_2 \geq M_1) = \sup_{y \geq x}[\min(\mu_{M_1}(x), \mu_{M_2}(y))] \tag{8}$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & if \quad m_2 \geq m_1, \\ 0, & if \quad l_1 \geq u_2, \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases} \tag{9}$$

where *hgt* is the height of the intersection of M_1 and M_2, *d* is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} (see Figure 3). To compare M_1 and M_2, both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are required.

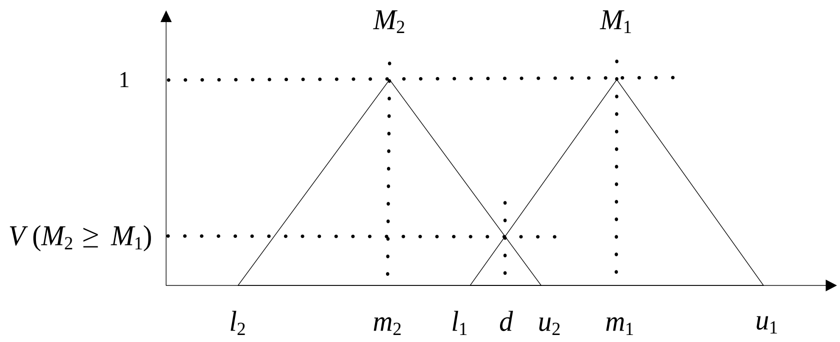

Figure 3. Intersection point *d* between two fuzzy numbers M_1 and M_2.

<u>Step 3</u>: The degree possibility of a convex fuzzy number to be greater than k convex fuzzy numbers M_i (for $i = 1, 2, ..., k$) can be defined by Equation (10).

$$V(M \geq M_1, M_2, ..., M_k) = V[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and} \ldots \text{and } (M \geq M_k)] = \min V(M \geq M_i), \quad i = 1, 2, ..., k \tag{10}$$

Assume that:

$$d'(A_i) = \min V(S_i \geq S_k) \text{ for } k = 1, 2, ..., n; \quad k \neq i \tag{11}$$

Next, the weight vector is given by Equation (12).

$$W'' = (d'(A_1), d'(A_2), ..., d'(A_n))^T \tag{12}$$

where $A_i \left(i = 1, 2, \ldots, n\right)$ has *n* elements.

<u>Step 4</u>: The normalised weight vectors are defined as:

$$W = (d(A_1), d(A_2), ..., d(A_n))^T \tag{13}$$

where W is a non-fuzzy number.

3.3. Step 3: Fuzzy AHP Phase for criteria weights

At the third step, the decision makers do pairwise comparisons in a linguistic form in order to obtain criteria weights. The linguistic forms are converted into triangular fuzzy numbers for Fuzzy AHP evaluations that use the same procedure as presented in Step 2. Fuzzy comparisons are defuzzified with Chang's extent analysis (1992) and the criteria weights are obtained by the Fuzzy AHP phase. Table 1 is used for pairwise comparisons as in Step 2. Next, the fuzzy values of paired comparison are converted into crisp values via the Chang's extent analysis (1992). The overall weight are calculated using the Additive Weighted Aggregation (AWA) operator (Xu 2009) as shown in Equation (14).

$$g_i = \lambda_k * g_{ik} \tag{14}$$

where $i = 1,....I$ represents the criteria, $k = 1,....K$ represents the decision makers, λ_k is the weight of the k^{th} decision maker, and g_i is an aggregated group decision value of the i^{th} criterion function. After this aggregation phase, a unique matrix is obtained for criteria weights.

3.4. Step 4: TOPSIS phase

TOPSIS, one of the classical MCDM methods, was proposed by Hwang and Yoon (1981). TOPSIS is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution (PIS), and the farthest from the negative ideal solution (NIS), for solving a multiple criteria decision-making problem. The various J alternatives are denoted as $A_1, A_2, ..., A_J$. For the alternative A_j, the rating of the i^{th} aspect is denoted by f_{ij} as the value of the i^{th} criterion function for the alternative A_j. Assuming that n is the number of criteria, the TOPSIS procedure consists of the following steps:

<u>Step 1:</u> Calculation of the normalised decision matrix**.**

The normalized decision matrix r_{ij} is calculated as:

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{J} f_{ij}^2}} \qquad j = 1, 2, ..., J \qquad i = 1, 2, ..., n \tag{15}$$

<u>Step 2:</u> Calculation of the weighted normalized decision matrix.

The weighted normalized decision matrix v_{ij} is calculated as:

$$v_{ij} = w_i * r_{ij} \qquad j = 1, 2, ..., J \qquad i = 1, 2, ..., n \tag{16}$$

where w_i is the weight of the i^{th} attribute or criterion, and $\sum_{i=1}^{n} w_i = 1$

<u>Step 3:</u> Determination of the ideal and negative-ideal solutions.

The ideal and negative-ideal solutions, respectively $A*$ and $A-$, are determined as follows:

$$A^* = \left\{v_1^*, ..., v_i^*\right\} = \left\{(\max_j v_{ij} \mid i \in I'), (\min_j v_{ij} \mid i \in I'')\right\} \tag{17}$$

$$A^- = \left\{v_1^-, ..., v_i^-\right\} = \left\{(\min_j v_{ij} \mid i \in I'), (\max_j v_{ij} \mid i \in I'')\right\} \tag{18}$$

Where I' is associated with the benefit criteria, and I'' is associated with the cost criteria.

Step 4: Calculation of the separation from the ideal solution.

The separation measures are calculated using the n-dimensional Euclidean distance. The separation of each alternative from the ideal solution is given as follows:

$$D_j^* = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^*)^2} \qquad j = 1, 2, ..., J \tag{19}$$

Similarly, the separation from the negative ideal solution is given as:

$$D_j^- = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^-)^2} \qquad j = 1, 2, ..., J \tag{20}$$

Step 5: calculation of the relative closeness to the ideal solution.

The relative closeness of the alternative a_j is defined as:

$$CC_j^* = \frac{D_j^-}{D_j^* + D_j^-} \qquad j = 1, 2, ..., J \tag{21}$$

Step 6: Ranking of the preference order. The preference order is simply ranked according to the work of (Opricovic and Tzeng 2004).

Step 7: Application of TOPSIS.

This step starts by establishing fuzzy evaluations of the alternatives with respect to the individual criteria by using TFNs. A decision matrix indicating the performance ratings of the alternatives according to the criteria is then obtained. The linguistic scales and their corresponding fuzzy numbers are used as follows: (1,1,1)-very poor, (2,3,4)-poor, (4,5,6)-fair, (6,7,8)-good, (8,9,10)-very good. Each decision-maker achieves the evaluation in a linguistic form and obtains the alternatives' performances. A defuzzification is then done using the formula in Equation (22) (Xu & Chen, 2007)

$$\bar{f}_{ijk} = \frac{1}{2}\left[f_{ijk}^{l} * (1 - \eta_{ijk}) + f_{ijk}^{m} + f_{ijk}^{u} * \eta_{ijk} \right] \tag{22}$$

where f_{ijk} is the fuzzy value of i^{th} criterion function for the alternative A_j for the k^{th} decision maker, f_{ijk}^{l} represents the lower value, f_{ijk}^{m} represents the medium value, f_{ijk}^{u} represents the upper value of f_{ijk} and $\bar{f}_{ijk}$ is the defuzzified value of f_{ijk}. A new way is proposed here to calculate the coefficient η_{ijk} for the k^{th} decision maker of the i^{th} criterion for the alternative A_j. The idea is inspired from the calculation of the relative degree of similarity adapted from Olcer and Odabasi (2005). The principle is to determine this value regarding to the distance between the decision-makers' evaluations. If a decision-maker's evaluation is closer to the group evaluation, then her/his upper fuzzy value has a higher impact. On the other hand, if a decision-maker's evaluation is far from the group evaluation, then her/his upper fuzzy value has lower impact. This calculation procedure makes the proposed methodology more realistic. For calculating the relative degree of similarity, the degrees of similarity, the similarity matrix, and the average degree of similarity have to be calculated respectively. To obtain the degree of similarity value of the p^{th} decision maker to the r^{th} decision maker, S_{pr} is calculated as in Equation (23)

$$S_{pr} = 1 - \frac{\left|f_{ijp}^{l} - f_{ijr}^{l}\right| + \left|f_{ijp}^{m} - f_{ijr}^{m}\right| + \left|f_{ijp}^{u} - f_{ijr}^{u}\right|}{3} \tag{23}$$

which forms the agreement matrix *AM* as shown in Equation (24)

$$AM = \begin{bmatrix} 1 & S_{12} & \cdots\cdots & S_{1K} \\ : & 1 & : & S_{2k} \\ : & : & 1 & : \\ S_{K1} & S_{K2} & \cdots\cdots & 1 \end{bmatrix} \qquad \forall i, j \tag{24}$$

To obtain the average degree of similarity, AA_p is calculated using Equation (25).

$$AA_p = \frac{1}{K-1} \sum_{\substack{r=1 \\ p \neq r}}^{K} S_{pr} \qquad p = \{1, \ldots\ldots, K\} \qquad \forall i, j \tag{25}$$

Last, the relative degree of similarity η_{ijk} is calculated as shown in Equation (26).

$$\eta_{ijk} = \frac{AA_p}{\sum_{p=1}^{K} AA_p} \qquad \text{where} \qquad p = k \qquad \forall i, j \tag{26}$$

In calculating η_{ijk} in this way, the degree of similarity of each decision maker is included in the defuzzification step. These individual decision matrices are aggregated into a group decision matrix by using the AWA operator (Xu 2009) using Equation (27)

$$f_{ij} = \lambda_k * \overline{f}_{ijk} \tag{27}$$

where $i = 1, 2, \ldots, I$ represents the criteria, $j = 1, \ldots, J$ represents the alternatives, $k = 1, \ldots, K$ represents the decision makers, λ_k is the weight of the k^{th} decision maker and f_{ij} is the aggregated group decision value of i^{th} criterion function for the alternative A_j. Following this aggregation phase, only one group decision matrix is obtained.

4. Application on the selection of experts for humanitarian development projects

4.1. Weights of the decision makers and criteria's

The case discussed in this paper is related to the evaluation and selection of experts for a humanitarian development project in Africa proposed by one of the several United Nations offices. The consultancy concerns the reduction of poverty in a rural area, in accompanying and coaching a group of women, producing handmade embroideries. The project is devoted to build up and structure complete value chains that could help this specific population to provide their products on the market and manage them using the most adequate business development techniques. Four decision makers participate in the humanitarian expert selection procedure from the same department according to the rules specified by the United Nations (United Nations 2010). The office is in charge of funding, hiring the expert, and controlling the execution of the project. Five candidates considered as alternatives applied for the job. The decision maker who has a better knowledge of the rest of decision makers is asked objectively to assess each one's importance according to their respective levels of expertise and to make a pairwise comparison between the decision makers (DM i, i = 1,…,4) on a linguistic scale basis. The linguistic assessments are then converted into triangular fuzzy numbers for FAHP evaluations, using the transformation procedure in Table 2. The results are shown in Table 3, where each 3-uplet is a triangular fuzzy number. By applying FAHP, the different weights of the decision makers in the selection process are obtained in Table 4. This process reaches a situation where the weights of the decision makers have different values. In that case, DM 2 is taking almost half of the decision importance in the selection process with a weight equal to 0.449.

Equal Importance	0.33	1,00	3,00	**1~ = (1/3, 1, 3)**
Weak Importance	1,00	3,00	5,00	**3~ = (1, 3, 5)**
Strong importance	3,00	5,00	7,00	**5~ = (3, 5, 7)**
Very strong importance	5,00	7,00	9,00	**7~ = (5, 7, 9)**
Extremely preferred	7,00	9,00	9,00	**9~ = (7, 9, 9)**

Table 2. Representation of triangular fuzzy numbers.

	DM 1			**DM 2**			**DM 3**			**DM 4**		
DM 1	1	1	1	0.20	0.33	1.00	1.00	3.00	5.00	3.00	5.00	7.00
DM 2	1.00	3.00	5.00	1	1	1	3.00	5.00	7.00	3.00	5.00	7.00
DM 3	0.20	0.33	1.00	0.14	0.20	0.33	1	1	1	0.20	0.33	1.00
DM 4	0.14	0.20	0.33	0.14	0.20	0.33	1.00	3.00	5.00	1	1	1

Table 3. Pairwise comparisons of the expertise of the decision makers.

DM 1	0.360
DM 2	0.449
DM 3	0.015
DM 4	0.176

Table 4. Final weights of the decision makers.

Similarly to the process providing the weights of the decision makers, the criteria weights are calculated. It is feasible when all the decision makers complete the tables comparing the different criteria. Each decision maker assesses the importance of each criterion compared to the others and fills in the corresponding table. By comparing the criteria and after the application of FAHP, the weight of each criterion is obtained. The different criteria weights are illustrated in Table 5 with:

- **C3**: Satisfaction with past projects: This criterion has the highest weight (0.264) and corresponds to the objective of giving a maximum insurance to achieve the humanitarian development project objectives through qualified experts, who successfully accomplished their previous assignments.
- **C1**: Work experience: The second highest weight is given to the criterion 'Work experience' (0.251), which is too close to the weight of C3 (0.264). This is because those two criteria represent complementary concepts linked to the satisfaction with past work in which the expert was involved.
- **C4**: Motivation: Motivation is an important criterion (equal to 0.237) in the selection of experts that will handle humanitarian projects due to the nature of the job, where the expert can be granted a limited budget and has to face difficult working conditions.
- **C6**: Integration capacity: This criterion is ranked fourth with an important weigh of (0.171). Thus, the expert ability of integrating and leading a team in such a job of a delicate nature is a key factor in the selection process.
- **C2**: Education: Related to the educational background and diplomas obtained by the expert, this criterion has a weight of (0.077).
- **C5**: Compensation: Surprisingly, the results show a null weight for the criterion C5 'Compensation' (financial remuneration). This is explained by the fact that on the one hand, the office offers remuneration on the basis of a predefined fixed scale with limited reimbursement of the travel and subsistence expenses. On the other hand, the office limits the time schedule within which the project has to be developed and implemented. Thus, the remuneration is more or less the same for all candidates and has no significant influence on the selection process.

The TOPSIS phase consists of evaluating the experts by each decision maker according to the six criteria. For this evaluation, the fuzzy linguistic variables shown in Table 6 are used.

C1	Work experience	0.251
C2	Education	0.077
C3	Satisfaction with past projects	0.264
C4	Motivation	0.237
C5	Compensation	0.000
C6	Integration capacity	0.171

Table 5. Defuzzified criteria weights.

Very good	0.8	1	1
Good	0.6	0.8	1
fair	0.4	0.6	0.8
Poor	0.2	0.4	0.6
Very poor	0	0.2	0.4

Table 6. Definition of triangular fuzzy numbers for TOPSIS.

The process is based on the calculation of the degree of similarity for the five experts (Step 2), the matrix of degree of similarity (Step 3), the defuzzified matrix (Step 4), the aggregated and defuzzified matrix which takes into account the Decision Makers' weights (Step 5) and the normalized matrix (Step 6), the weighted normalised matrix which takes into account the Criteria's weights (Step 7). Finally, we are able to find the Ideal-solution (A*) and the Negative-Ideal-Solution (A-) that are addressed in Table 7 for each criterion.

	A*	A-
C1	0.138	0.064
C2	0.047	0.010
C3	0.148	0.065
C4	0.141	0.065
C5	0.000	0.000
C6	0.108	0.034

Table 7. Ideal-solution (A*) and Negative-Ideal-Solution (A-) for each criterion.

As a result, the highest value related to the relative closeness to the ideal solution defines the best adequate expert for the considered activity, taking into account all the criteria and all the evaluations of the decision makers. According to the relative closeness to the ideal solution, the experts are ranked as shown in Table 8. The results show the superiority of Expert 3 with a CC* equal to 0.878. We can also notice that Expert 3 is far away from the second best expert, *Expert 1* (0.878 vs 0.557).

	D*	D-	CC*	Ranking
Expert 1	0.093	0.117	0.557	2
Expert 2	0.106	0.114	0.519	3
Expert 3	0.017	0.125	0.878	1
Expert 4	0.104	0.077	0.426	5
Expert 5	0.111	0.089	0.445	4

Table 8. Final ranking of the experts.

5. Sensitivity analysis

5.1. Sensitivity analysis of Decision-Makers weights

To analyse the quality of the methodology in reaching a good solution under different conditions, a sensitivity analysis is conducted. Two different situations are investigated. In the first situation, the defuzzification phase is addressed to identify the impact of the relative degree of similarities (η_{ijk}) on the results. In this investigation, each relative degree of similarity of the decision maker i is increased respectively by 25%, 50%, 100% and 200% for each alternative and criterion and noted respectively Ei-25, Ei-50, Ei-100 and Ei-200. While one decision maker's value is increased, the remaining values of the decision makers are decreased in a way that the total of the relative degree of similarities is equal to one for each alternative and criterion. The result of this test is given in Figure 4. The *x*-axis represents the increase in the decision maker i (i = 1...4) assessment's values in percentage and the *y*-axis represents the new relative closeness *CCj** values of the expert j, j=1…5.

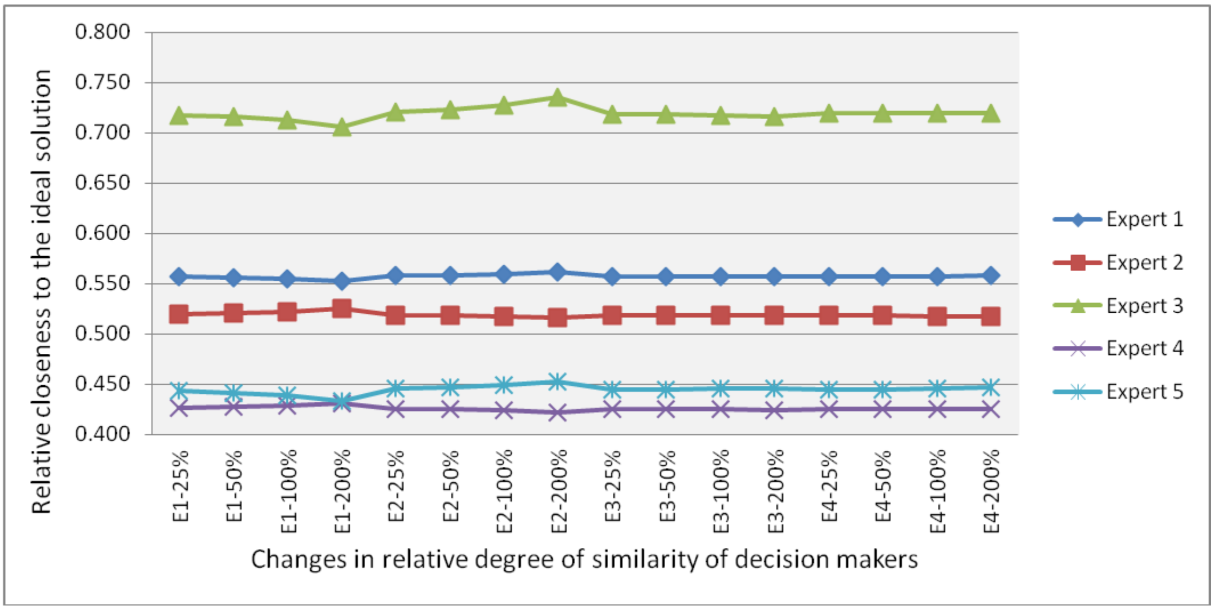

Figure 4. Sensitivity analysis of the decision maker's relative degree of similarity.

As shown in Figure 4, *Expert 3* remains the best candidate for the humanitarian development project in all calculations and cases. Even if there are small deviations in the calculations, the results are still consistent. Indeed, *Expert 3* has the highest CC_j* value with 0.735, reached when DM 2 relative degree of similarity value is increased by 200% (E2-200 in Figure 3). Furthermore, the lowest CC_j* value for the *Expert 3* is 0.706 calculated comparing all the tests. This value is obtained when the DM 1 relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The second best expert is *Expert* 1 with a highest CC_j* value of 0.561 obtained when DM 2 relative degree of similarity value is increased by 200% (E2-200 in Figure 3). The lowest CC_j* value obtained by *Expert 1* is 0.553 when the first Decision Maker's relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The third best candidate is *Expert 2* with the highest CC_j* value of 0.525 reached when DM 1 relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The lowest CC_j* value obtained by *Expert 2* is 0.516 when the DM 2 relative degree of similarity value is increased by 200% (E2-200 in Figure 3). The fourth best candidate is *Expert 5* where the highest CC_j* value is 0.453 reached when DM 2 relative degree of similarity value is increased by 200% (E2-200 in Figure 3). The lowest CC_j* value obtained by *Expert 5* is 0.433 in the calculation obtained when the DM 1 relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The last candidate *Expert 4* reached its highest CC_j* value of 0.431 when DM 1 relative degree of similarity value is increased by 200% (E1-200 in Figure 3). The lowest CC_j* value obtained by *Expert 4 is* 0.422 from the calculation conducted DM 2 relative degree of similarity value is increased by 200% (E2-200 in Figure 3).

From the results in Figure 4, we notice that the only change in ranking occurs when DM 1 relative degree of similarity value is increased by 200%. *Expert 4* (which was originally the last one) reaches this new context the fourth place, same as *Expert 5*. As a consequence, the ranking obtained through this approach is not significantly affected by the variation related to the degree of similarity of decision makers. Thus, we can conclude that in one hand, the proposed approach is robust since the similarity of the obtained rankings with the original ones especially for *Expert 1*, *Expert 2*, and *Expert 3*

In the second series of tests, the focus is put on the investigation of the effect of the decision maker's weights on the results. The tests are designed by increasing each original decision maker weight by 25%, 50%, 100% and 200%. While one decision maker's weight is increased, the remaining values of decision makers are decreased in certain amount in a way that the total of the weights is equal to one. The result of this sensitivity analysis is given in Figure 5. The x-axis represents the relative increase of the i^{th} decision maker weight E_i (i= 1...4) and the y-axis represents the new relative closeness CC_j* values of the expert j, $j=1 \ldots 5$.

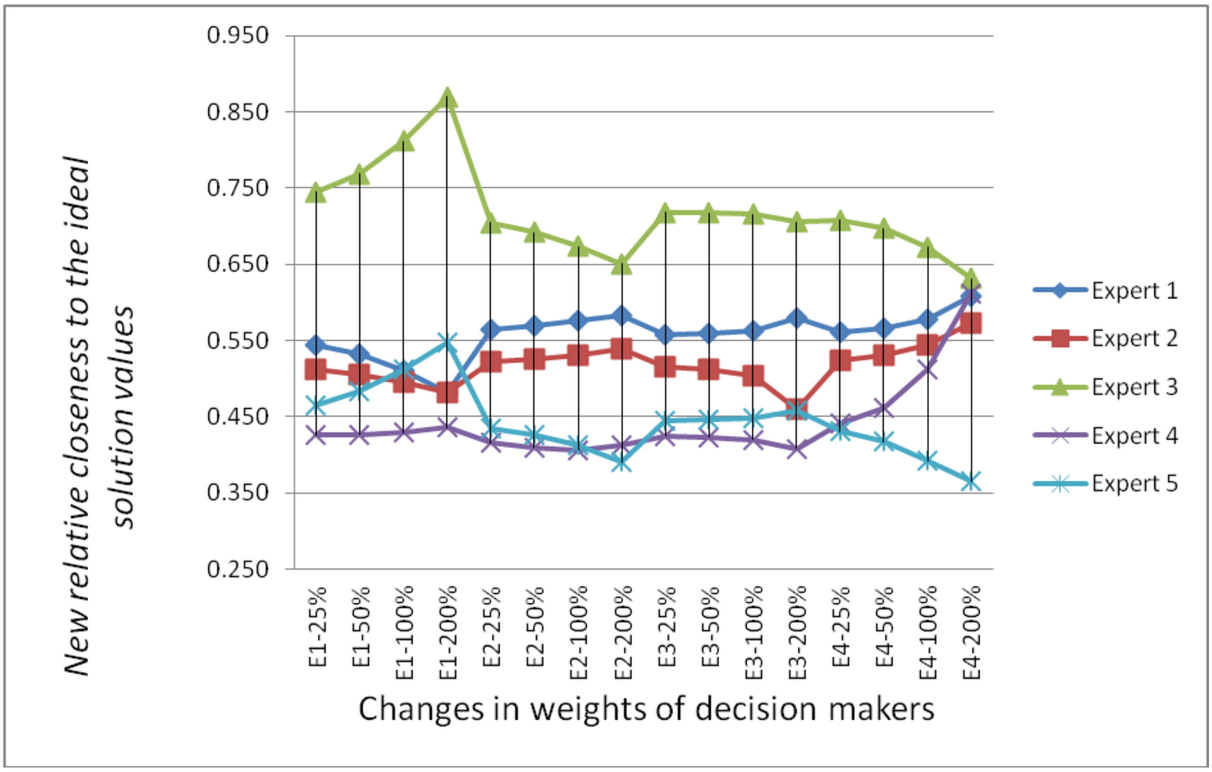

Figure 5. Sensitivity analysis of the decision maker's weights.

Similar to the variation of decision maker's degree of similarity and as shown in Figure 5, *Expert 3* remains the best candidate for the project throughout all the calculations and cases. Even if there are small deviations in the calculations, the results are still consistent. Indeed. *Expert 3* has the highest CC_j* value of 0.870, reached when DM 1 weight value is increased by 200% (E1-200 in Figure 4). Moreover, the lowest CC_j* value of the *Expert 3* in all the tests performed is 0.631, obtained when DM 4 weight value is increased by 200% (E4-200). The highest CC_j* value for *Expert 1 is* 0.608, reached when DM 4 weight is increased by 200% (E4-200), while the lowest CC_j* value is 0.482, obtained when DM 1 weight is increased by 200% (E1-200). The highest CC_j* value for the *Expert 2* is 0.574, reached when DM 4 weight value is increased by 200% (E4-200), while his lowest CC_j* value is 0.460 when DM 3 weight value is increased by 200% (E3-200). The highest CC_j* value for the *Expert 5* is 0.548, attained when DM 1 weight value is increased by 200% (E1-200), while his lowest value is 0.366 obtained when DM 4 weight is increased by 200% (E4-200). The highest CC_j* value for the *Expert 4* is 0.611, achieved when DM 4 weight value is increased by 200% (E4-200), while the lowest CC_j* value is 0.407, obtained if the weight of DM 3 increases by 100% (E3-200).

Moreover, the following observations were made:

- When the first decision maker's (DM 1) weight value is increased by 200% (E1-200%), *Expert 5* becomes the second best expert instead of the fourth one.
- When the second decision maker's (DM 2) weight value is increased by 200% (E2-200%), *Expert 4* becomes the fourth best expert instead of the last one.
- When the third decision maker's (DM 3) weight value is increased by 200% (E3-200%), *Experts 2* and 5 are on an equal level and both occupy the third place.

- When the fourth decision maker's (DM 4) weight value is increased by 25%, 50%, 100% and 200%, *Expert 5* (who was originally in the 4^{th} place) changes significantly his rank; a shift from the 4^{th} place to the last one. It is also noticed that for E4-200, the difference between *Expert 4, Expert2* and *Expert 3* is very small. Thus, the fourth decision maker (DM 4) has the most powerful influence on the rankings of the experts.

5.2. Sensitivity analysis of criteria weights

The experiments are based on the increase of each original criterion weight respectively by 25%, 50%, 100% and 200%. While one criterion's value is increased, the remaining values of criteria are decreased in certain amount such that the total of the criteria weights is equal to one. The result of this sensitivity analysis is given in Figure 6. The x-axis represents the increase in criteria weight's values in percentage with respect to the criteria itself *Ci* (i = 1...6) and the y-axis represents the new relative closeness to the ideal solution CC_j* related to the *Expert j* (j =1…5).

As shown in Figure 6, an expert rank changes according to the different criteria weights. Indeed, the best candidate depends on the criterion selected to be changed and on its variation. The results are not consistent in this case and they are very sensitive to the variation of criteria weights except for the criterion C5 which is the remuneration of the expert (see the data set C5-25%, C5-50%, C5-100%, C5-200% in Figure 5). In this case, the best candidate remains the *Expert 3*. This is due to the weight of the criterion 'Remuneration' that is originally null as provided by the fuzzy AHP evaluation done by the decision makers. In the variations context, we can notice through Figure 5 that *Expert 3* (who was originally the best expert) highest CC_j* value is given by (C3-200%) representing the increase of weight related to satisfaction from past projects while the lowest CC_j value is given by (C6-200%) corresponding to the integration capacity weight increase. *Expert 1* (who was originally the second expert) highest CC_j* value is given by (C1-200%) related to work experience weight. The lowest CC_j* value of *Expert 1* is obtained when the weight of the criteria related to satisfaction from past projects is increased by 200% (C3-200%)). The highest CC_j* value for *Exper*t 2 is also given by (C3-200%) while the lowest CC_j* value is given by the increase of the weight related to motivation criteria (C4-200%). *Expert 4* highest CC_j* value is obtained by (C6-200%) while the lowest CCj* value is given by (C1-200%) related to work experience criteria weight which is the same case of *Expert 5.* Thus, attention should be given to weighting the different criteria, since this step may significantly influence the final rank.

Figure 6. Sensitivity analysis of the criteria weights.

5.3. Comparison of the obtained criteria weights (FAHP) with ANP technique result

As mentioned above, we used in this paper Fuzzy AHP for criteria weights (Step 3) assuming that the six criteria are independent. However, since the work deals with experts, taking into account their complexity and diversity, Analytic Network Process (ANP) seems to be a good technique to be used for the criteria weight evaluation for comparison purposes. The advantage of ANP is the capability of solving the problems in which alternatives and criteria have such interactions that cannot be shown in a hierarchy. When decision makers decide to model a problem as a network, it is not necessary for them to specify the levels (Bauyaukyazici and Sucu, 2003). Indeed, in this case we assume that the six criteria for the humanitarian expert selection are dependent and affect each other, which is referred to as inner dependency (Saaty and Takizawa, 1986).

The different criteria weights obtained by ANP technique are illustrated in Table 9, where we notice that the ranking remains the same as the results obtained by our hybrid approach. C3 (Satisfaction with past projects) and C1 (Work experience) have more than half of the total criteria weights. C4 (motivation) comes in the 3rd place with an important weight equal to 0.128 (vs 0.237). C6 (Integration capacity) in the 4th place with a weigh of 0.088 (vs 0.171). C2 (education) comes in the 5th place with a weight of 0.061 (vs 0.77). Unlike the result obtained by our approach, C5 (compensation) comes with a weight of 0.043 (vs 0.000).

From a ranking point of view, this comparison validate our adopted approach. We can also notice that the fuzzy hybrid approach pushes the criteria values towards limits by increasing those having the highest ranking such as C3 and C1 (0.345 vs 0.264 and 0.332 vs 0.251) and decreasing the lowest ranking values like C2 and C5 (0.077 vs 0.061 and 0.043 vs 0.000) which allows to reduce uncertainty for decision makers.

C1	Work experience	0.332
C2	Education	0.061
C3	Satisfaction with past projects	0.345
C4	Motivation	0.128
C5	Compensation	0.043
C6	Integration capacity	0.088

Table 9. ANP criteria weights.

6. Conclusion

This paper aims to fill in the gap in literature with regard to expert selection during ad-hoc conditions in the humanitarian field. In fact, and to the best of the authors' knowledge, there have been no studies conducted on the match between expert's selections criteria and the requirements essential for humanitarian development projects. This paper would then contribute to this research area through developing a group decision-making approach to select experts for humanitarian development projects based on multiple subjective and objective criteria. This multi-criteria group decision-making approach paves the way for taking the best decisions possible in the process of experts' selection for humanitarian development projects.

Methodologically speaking, there are indefinite or ambiguous elements or criteria in the evaluation of experts and the assessment of their suitability for handling humanitarian projects. In this respect, one of the additional major contributions of the present study is the inclusion of both quantitative and qualitative evaluations for the different criteria through the use of fuzzy concepts. In fact, this hybrid approach is built on two stages: the first stage consists of fuzzy AHP for the criteria and decision makers' weights, and the second one implements TOPSIS to rate the candidates based on their relative closeness to the ideal solution. These aspects are characterized by specific criteria that have to be reflected to fulfil the requirements of the humanitarian organizations and agencies. Taking this into account in this work, six criteria were identified and recommended to be considered in the selection of experts and consultants for humanitarian projects development. These six criteria are: Work experience, Education, Satisfaction from past projects, Motivation, Compensation, and Capacity of integration.

The real study case discussed in this paper shows that in all the cases where the decision makers' weights or the relative degrees of similarity vary, the most competent candidate to be selected remains the same. This outcome applies likewise for most of the cases where there is an increase in the weights of the different criteria. Therefore, even if in some extreme cases, where the increase amounts to 200%, there could be a variation in the final candidates' ranks. Additionally, in order to corroborate the approach used to weight the diverse criteria, this paper assumes the existence of dependency between those elements. By way of comparison, an ANP technique is developed and the result indicates that the ranking of criteria is not affected. This demonstrates the robustness of the solutions provided by the hybrid approach. In fact, it

helps in opting for the decisions that are valid and useful in different scenarios and patterns taking into account alterations in weights of both the decision makers and the criteria. As a matter of fact and as demonstrated through the study case, the applied approach indicates a high rank associated with *Expert 3*. Accordingly, the decision makers selected *Expert 3* for a deep interview which obviously confirms the results of the study. The conducted interview proved that *Expert 3* satisfies the requirements of the job, with respect to the six designated criteria, guaranteeing an optimal accomplishment of the humanitarian development project objectives. Besides, the democratization of the selection process through the integration of the opinions of all decision makers, regardless of their areas of expertise or specific roles, sets the ground for common responsibility and commitment in monitoring the tasks and funds allocated for the execution of the project. Thus, such a hybrid approach can effortlessly increase the objectivity and awareness in the staffing processes of experts for humanitarian development projects and lead to an unbiased and equal treatment for the candidates who apply for this type of job.

In spite of the fact that the different decision makers' contributions have been assessed by a unique decision maker who has a prior knowledge of the expertise and skills of all other decision makers, it is not possible to always guarantee the same circumstance. Therefore, one of the potential future research directions entails the implementation of a cross evaluation process; a process where each decision maker evaluates and is evaluated by other members of their team. The final weight of each decision maker is then calculated with regard to all the evaluations provided during this procedure. Also, the proposed methodology can be improved with the incorporation of some modifications and can be used for other problems related to the humanitarian field. It can be combined with mathematical models in order to improve results in the decision-making process related to selection problems such as emergency facility location and selection based on the opinion of experts, with the possibility of using fuzzy TOPSIS in order to present to DMs a robust tool for decisions under uncertainty.

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